Divide and Conquer: Partitioning Online Social Networks

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ABSTRACT

Online Social Networks (OSNs) have exploded in terms of scale and scope over the last few years. The unprecedented growth of these networks present challenges in terms of system design and maintenance. One way to cope with this is by partitioning such large networks and assigning these partitions to different machines. However, social networks possess unique properties that make the partitioning problem non-trivial. The main contribution of this paper is to understand different properties of social networks and how these properties can guide the choice of a partitioning algorithm. Using large scale measurements representing real OSNs, we first characterize different properties of social networks, and then we evaluate qualitatively different partitioning methods that cover the design space. We expose different trade-offs involved and understand them in light of properties of social networks. We show that a judicious choice of a partitioning scheme can help improve performance.

1. INTRODUCTION

The last few years have seen wide-scale proliferation of Online social networks (OSNs). According to a recent study, OSNs have become more popular than email [16] and popular OSNs like Facebook, MySpace, Orkut etc. have tens of millions of active users, with more users being added by the day. Twitter, for instance, grew a remarkable 1382% in one month(Feb-Mar 09) [17]. The growth of OSNs pose unique challenges in terms of scaling, management and maintenance of these networks [8]. In addition, online services are moving towards an increasingly distributed cloud paradigm [13, 6, 4], that bring forth their own challenges since smaller and geographically spread data centers [6] will increase network costs.

One obvious solution to deal with scaling issues would be partition the social network graph and assign partitions to different servers. However, given the unique properties of social network graphs (presence of clusters or communities, skewed degree distributions, correlations to geography), it is not entirely clear how to partition such graphs, what properties of the underlying social network graph need to be taken into account and what are the trade-offs involved in partitioning. Understanding the design space and the trade-offs can help in making informed choices.

The main contribution of this paper is to provide an understanding of the problem of social network partitioning by relying on measurements taken from two large and popular social networks: Twitter and Orkut. We state the problem of social network partitioning along with the performance objectives, highlighting the trade-offs involved. We then discuss the different characteristics of social network graphs that can impact design choices of partitioning algorithms. In particular, using the data we obtain for the Twitter network, we measure strong geographical locality as well as heterogenous traffic patterns between users.

Based on the performance objectives and social network characteristics, we select the following partitioning algorithms to evaluate against our data-sets. We first choose METIS [10] that is drawn from traditional graph partitioning algorithms [9, 10, 23]. This is an intuitive choice as these algorithms are designed to produce partitions while reducing traffic across partitions and balancing the number of nodes across partitions. Since it is widely known that social networks consist of 'community' structure [14, 21], the next method we evaluate relies on extracting such communities, and these communities can be used as partitions. However certain issues with such algorithms, in particular arbitrary number of communities and skewed partition sizes, lead us to augment an existing community detection scheme to deal with these issues. We evaluate these algorithms against different performance metrics to expose various trade-offs, in particular the trade-off between balancing load across different partitions and reducing traffic between partitions. After evaluating different algorithms against our datasets, we find that the augmented community detection that we devised does well in terms of balancing the trade-offs involved and we interpret these results in light of properties that social networks possess.

2. RELATED WORK

Graph partitioning has been proposed to deal with scaling issues of social network systems [8, 7], as well as handling large data-sets [27]. However, to the best of our knowledge, there is no study of different properties of social network graphs, how these properties can impact the possible different choices of partitioning al-

gorithms and how different partitioning algorithms perform on real data, along with quantifying the different tradeoffs involved. We aim to address these concerns in this paper.

There has been a concerted effort to characterize and understand Online Social Networks over the last few years [18, 3, 25, 12, 19], including flow of information [11], existence of social communities [14] as well as evolution of such networks [18, 1]. As such, we are more focused on understanding the aspects of social networks that can impact partitioning. Towards that end, we rely on certain results (like existence of social communities [14, 20]) that have been reported in the past and also report existence of certain properties (like geographical locality and heterogenous traffic distribution) in one network we study; Twitter [12] that can better inform system architects interested in social networks, as well as design of partitioning schemes.

In order to understand the trade-offs involved, we rely on different partitioning schemes that span a range of design choices. We first focus on a method drawn from classical graph partitioning algorithms [9, 10, 23, 24] that rely on finding minimum edge cuts to seperate the graph into roughly equal-sized clusters. We also draw from work done that aims to extract 'communities' that are socially relevant [21, 2]. However these algorithms do not give a desired size of communities, nor do they give equal sized partitions. We present a scheme in this paper that yields a desired number of communities, of equal size.

3. METHODOLOGY

In this section, we pose the problem of social network partitioning, along with the objectives. We then explore properties of social network graphs that could impact the design and choice of different partitioning schemes. We end this section with a brief description of some of the methods we explore in this study. We first describe the data-sets that we collect and use.

3.1 Data

In order to carefully understand the different characteristics of social network graphs that can impact partitioning, we rely on data. There exist data-sets of large social networks that are publicly available [19]. However, we were looking for data-sets that included location information, as well as information about traffic that is exchanged between users. Since we are not aware of any publicly available data-sets, we collected our own data-set by crawling Twitter (http://www.twitter.com). Twitter is a microblogging site that has become very popular of late. More details about Twitter, along with information on how links are formed, can be found in [12]. We collected data from Twitter between Nov 25 - Dec 4, 2008 and collected information comprising 2, 408, 534 nodes and 38, 381, 566 edges (although Twitter has directed edges, we report total edges and use edges as undirected unless otherwise stated).

In addition, we also collect location information, as

self-identified by users. This can be in the form of freetext or by latitude/longitude. In order to glean locations, we had to filter the free-text for junk information. After basic preprocessing we obtained 187K different locations for the 996K users where the location text was meaningful. We then used the Yahoo! Maps Web Services¹ that offers the Yahoo Maps functionality as an API to standardize locations. We could test the 187K different locations to obtain the country, and where available, the state and the city. We finally obtained the standardized locations for 691K users.

We also collected traffic on Twitter in the form of 'tweets' (total 12M tweets) between the 2.4M users by using the Twitter API². From the tweets, we mined the following relevant fields: tweet_id, timestamp, user_id, location and content. This information allows us to get traffic information for every user and how this traffic is distributed across users (this gives us volume of social conversations). Approximately 25% of the population (587K) generated at least one tweet, for the rest of the users the Twitter API did not return tweets in the 19-days period under examination. Fig. 1(a) and (b) show the skewed distribution of the number of links per user as well as the volume of traffic sent per user. We intend to make this data public.

We also use graphs representing other social networks, including Orkut, that can be taken to be closer to an actual 'social' network, as edges in such a graph will probably represent actual social relationships. This dataset consists of 3,072,441 nodes and 223,534,301 edges and this data was collected between Oct 3 - Nov 11, 2006. More information can be found in [19]. We present results from Twitter and Orkut in this paper for space reasons, although our analysis on other graphs [19] have borne similar results.

3.2 Social Network Partitioning

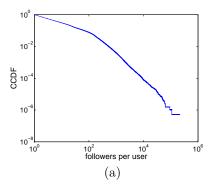
We represent a social network as a graph G=(V,E), where the edges are undirected. The problem then is to partition V into k subsets or clusters, $(V_1,V_2,...,V_k)$, k>1 such that $V_i\cap V_j=\emptyset$ when $i\neq j$ and $\cup_i V_i=V$. The objective function to decide how to obtain these k partitions differ.

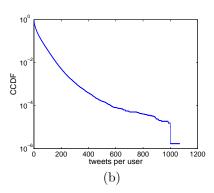
Performance Objectives The first objective function for a partitioning scheme would be to reduce the edges that traverse between partitions. We refer to these edges as external or *inter*-edges. This metric represents the amount of traffic that could traverse between partitions and reducing this metric therefore, has a direct bearing on reducing bandwidth costs. Bandwidth costs can be a bigger concern if a social network graph is hosted across geographically distributed data-centers [13].

The second objective function is related to keeping utilization high and balanced across servers hosting different partitions. Ideally, all partitions should be of

¹http://developer.yahoo.com/maps/rest/V1/geocode.html

²http://apiwiki.twitter.com





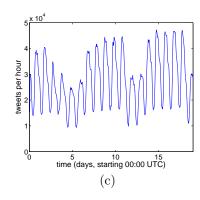


Figure 1: Twitter Characteristics (a) CDF of Followers (b) CDF of 'Tweets'/Messages per user (c) 'Tweets' per hour

equal size, leading to balanced utilization across machines. It has been noted that given the costs of server installation and limited lifetime, keeping servers on and running optimizes work per investment dollar [6]. By assigning nodes to different servers (equivalent to assigning partitions) in an informed manner can help achieve this goal.

Balancing load across servers and reducing inter-server traffic are often at odds with each other and hence there is a need to study the design space of partitioning schemes to characterize the tradeoffs involved. In addition, social networks have slightly different underlying characteristics compared to regular communication networks that can be exploited for the design of partitioning schemes. We discuss these characteristics in the next section.

3.3 Properties of Social Networks

Properties that can be relevant to the problem of partitioning are:

Structural Properties: Social networks are known to have skewed degree distributions, assortativity [20], small world properties [26] as well as strong clustering or *community* structure [14]. Partitioning by uncovering communities in a social network can be intuitively appealing as volume of intra-community interaction is much higher than inter-community interaction.

Geo-Locality Properties: Social networks have been shown to have strong correlations to geography; the probability of new links forming is correlated to distance [15]. We observe similar strong correlations to distance in the Twitter data-set. In Table 1, we present locality results of the top 5 countries and US states by size. We consider directed links. The second column shows the size distribution of different countries; for instance US has 60.2% of the total nodes. We also found the percentage of edges are closely correlated to the size of the network, for instance 66% of the total inlink edges and 65.01% of the total outlink edges belong to the US. The next two columns represent the percentage of inlinks and outlinks that come from users of the same country. For instance, 80% of inlinks in US come from nodes belonging to US, and 81% of outlinks in US also

belong to nodes within US. If we compare these numbers to the relative sizes of the partitions, we realize that there is high *geo-locality*; for a partition the percentage of links that are local is higher than what would be the case if connectivity is purely random; for instance in the case of US this would be 60.2% Factoring this locality property could yield performance benefits, specially if partitions are assigned to servers distributed geographically [6, 4]. Strong locality can thus reduce inter-server traffic considerably.

In addition, relying on semantic information like geographical location for partitioning can be appealing due to the simplicity as one does not need global information about the structure of the social network, and issues like *churn* (users joining/leaving the social network) can be handled more effectively and efficiently. We do not propose a scheme based on geographical locality in this paper and leave it for future work. However, we note that the community structure embeds some information about locality [15].

Traffic Properties: Traffic on social networks primarily consists of messages, user-generated content (UGC) and status updates exchanged between nodes. From our analysis of traffic on Twitter, we observed some similarities to traffic on IP networks like diurnal patterns (Fig.1(c)). However there are a few facets that makes traffic on social networks unique, and hence worth paying special attention to. First of all, traffic in social networks is inherently local; most traffic is confined to one-hop distance. Secondly, traffic in social networks can have a multiplicative effect due to the broadcast nature of certain messaging protocols like status updates. To illustrate this point, consider Figs.1 (a, b). These figures show the skewed nature of the number of followers (social contacts) a user in Twitter has, as well as the skewed nature of the number of messages (tweets) sent per user. Given the broadcast nature of status updates in Twitter, the 12M unique tweets, coupled with the skewed distribution of the number of followers, the actual number of tweets are in excess of 1.7B messages.

In addition, we also extracted *conversations* between users using the content in tweets; we establish a link between user i and j iif i-id appears in the content of

Country	Size (%)	% of inlinks	% of outlinks
US	60.2	79.9	81.0
GB	6.3	32.9	31.8
CA	4.02	26.7	25.2
BR	3.0	65	62.2
JP	2.9	80	83

State	Size (%)	% of inlinks	% of outlinks
CA	16.9	32	37
NY	8.3	22	25
TX	7.2	28	28
FL	4.6	19	17.6
IL	4.1	20	20

Table 1: Presence of Strong GeoLocality (Countries and US States): Twitter

at least one tweet of j and vice-versa. We obtain 265K links between people who are maintaining a conversation, which is clearly less than the 38M links between people according to the followers SN.

This information captures the social network at a finer level than the social network given by a simple contact list; people have users in ones' contact list that they may not actually know [3]. Conversations imply a more deeper social relation, therefore they can be used to validate the accuracy of the partition algorithms in preserving such strong social relations.

Algorithm 1 MO+

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Input: G = \langle V, E \rangle Social network graph
Input: k Number of final partitions
Input: \mathcal{F} Modularity optimization algorithm
Output: P Partition set, p_i set of nodes of partition
i, |P| = k
U \leftarrow \{\{1..|V|\}\}
while U \neq \emptyset do
    G' \leftarrow \langle V \backslash v_i \notin U_1, E \backslash e_{ij} \mid v_i \notin U_1 \vee v_j \notin U_1 \rangle

C \leftarrow \mathcal{F}(G') — partition algorithm
    C' \leftarrow C \mid |c_i| \ge |c_{i+1}| — sort the best partition by
    size
   for c_i \in C' do
if |c_i| > \frac{|V|}{k} then
U \leftarrow U \cup \{c_i\}
        else
            for p_j \in P do
               if c_i \neq \emptyset \land \left( |p_j| + |c_i| \le \frac{|V|}{k} \right) then p_j \leftarrow p_j \cup c_i c_j \leftarrow \emptyset
                end if
            end for
        end if
    end for
    U \leftarrow U \setminus \{U_1\}
end while
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3.4 Partitioning Methods

In order to explore the design space for partitioning algorithms and quantify the tradeoffs involved, we study the following methods:

Graph Partitioning (GP) Algorithms: The objective function that these algorithms rely on is to reduce inter-cluster edges; reduce the number of edges incident on vertices belonging to different clusters. In addition, the partitions should be balanced; have simi-

lar sizes. Hence such algorithms are a natural candidate to study as the performance objectives for our problem are addressed by such algorithms. Spectral partitioning algorithms rely on finding the minimum cut to ensure the minimum number of edges cross between partitions [9]. Many different variants have been proposed and we rely on the Multi-way partitioning method, also called METIS[10] that has been shown to produce very high quality clusters in a fast and efficient manner.

Modularity Optimization (MO) Algorithms: Social graphs with communities are intuitively different from random graphs in terms of structure [20]. This difference can be captured via a metric called modularity (Q) that is defined as the difference between the number of edges within communities and the expected number of such edges. Mathematically, $Q \sim A_{ij} - P_{ij}$, where A_{ij} is the actual number of edges traversing two communities, and $P_{ij} \sim d_i * d_j$, where d_i is degree of node i. The modularity metric is between (0,1) and lower values signify a structure closer to random graphs, while higher values signify strong community structure. The algorithms developed for community detection therefore rely on finding partitions that maximize this metric. For the purposes of this study, the modularity optimization scheme we use is proposed in [2], that suits our purpose and is capable of handling large graphs, very quickly. However, there are a couple of caveats: the communities can be unequal in size - this is closer to reality as real-life communities are seldom of equal size. The other problem is that there can be an arbitrary number of communities, as the objective of such algorithms is to find the natural number of communities, rather than find a predefined number. When we ran the algorithm on our datasets, we got 2743 and 37 communities for Twitter (modularity=0.48) and Orkut (modularity=0.63) respectively, with highly skewed community sizes (size of largest community were 21% and 25% of the total number of nodes), making these scheme not amenable for using as-is.

Modularity Optimization Enhanced (MO+):

In order to obtain a predefined and fixed number of communities, each community of a fixed size, we modify the results obtained by a modularity optimizing algorithm. In order to obtain a predefined number of partitions of equal size we devised the algorithm MO+ 1 that can be applied as a post-processing step to the results of a modularity optimization algorithm MO. At a high level, we start grouping the communities in a partition (with a predefined size) sequentially until the partition

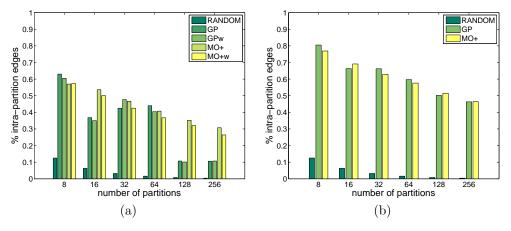


Figure 2: Partitioning Results: %of Intra-Partition Edges vs # of Partitions (a) Twitter, (b) Orkut

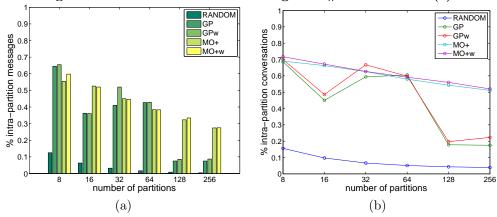


Figure 3: Partitioning Results with Traffic: %of Intra-Partition Edges vs # of Partitions (a) Twitter, (b) Conversations

is full, when we move to next available partition. In the case the community does not fit, we apply MO to the subset graph recursively. This scheme is extremely simple and naive, but for our purpose, it suffices.

Random Partitioning: As a baseline scheme, we also consider partitioning randomly. Random partitioning has few advantages - in addition to being very simple to implement, randomization balances load optimally. Hence if we are only concerned with balancing load, then random partitioning will give the best results. However such a scheme may not do well in reducing inter-partition traffic.

4. EXPERIMENTS

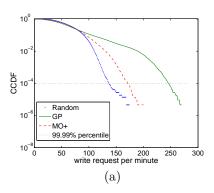
The algorithms we try out include Random (R), Graph Partitioning (GP), Modularity Optimization+ (MO+) for Twitter and Orkut. GPw and MO+w stand for the weighted versions of GP and MO+, where the weight can represent traffic on edges. We use the average of the number of tweets of exchanged between users; in the case that edge weight is 0, we set the weight to 1 to avoid disconnecting the graph. We study the effect of weighted edges for Twitter only since we do not have access to the traffic of Orkut.

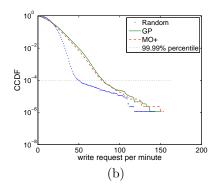
4.1 Communication across Partitions

We first evaluate how different partitioning schemes perform in terms of the number of a) edges, b) messages and c) conversations that exist within partitions. Note that higher the *intra*-partition, lower the network traffic between machines.

Intra-Partition Edges: Fig. 2 depicts the percentage of *intra*-partition edges. First of all, this metric is low for the Random, and it decreases as k^{-1} where k is the number of partitions. The other schemes decrease at a much slower rate showing that they are able to maintain the structure of the underlying social network. In network traffic terms, Random with 256 partitions results in a mere 0.4% of intra-partition edges, while GP and MO+ produce 10% to 30% of intra-partition edges for Twitter. For Orkut, the reduction on network traffic is even higher - both GP and MO+ produce around 50%intra-partition edges. GP and MO+ yield very similar results for Orkut and Twitter with small-size partitions. However, MO+ (and the weighted counterpart MO+w) seems to be more consistent across different number of partitions.

Intra-Partition Messages: For the next set of results, we use actual actual traffic, in the form of mes-





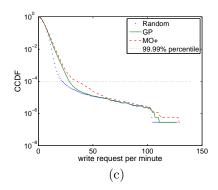


Figure 4: Distribution of Peak Load (a) 8 (b) 32 (c) 128

sages exchanged (1.7B messages, as reported in Sec. 3.3) and run them against the partitions produced. Here we use directed edges. Note that this is qualitatively different from merely counting the number of edges. Fig. 3 (a) shows intra-partition messages and the results are qualitatively similar to results in Fig. 2. Again, MO+gives better partitions than GP when the number of partitions increase and both of them perform better than Random.

Intra-Partition Conversations: Conversations link people who are likely to have a stronger social relationship, and therefore, they are more susceptible to consume each others user generated content [5, 22], e.g. videos, pictures, etc. Thus, it can be extrapolated that these links will generate additional traffic besides messages that we capture. The 265K conversational links also serve as a ground-truth. We expect the social network based partition schemes to be able to retrieve a majority of these strong links. Fig. 3(b) shows that the percentage of conversations is higher than the intrapartition edges; MO+ retains more than 50% of these social links even when the number of partition is 256, stressing the importance of using schemes that are more aware of the underlying social structure.

4.2 Partitions: Balancing Load

We showed that partitions based on the network structure(GP, MO+) can significantly reduce network traffic while compared to a Random. However, we also need to study the effect of these schemes on the load distribution across the machines that host these partitions. We extract the distribution of the arrival of tweets per minute from the trace we have. ³ If there was no partitioning, a single machine should be dimensioned (CPU, memory, I/O) to deal with an average of 448 write requests/min. Most systems rely on worst-case provisioning. In order to perform worst-case analysis, we extracted the 99.99% percentile traffic rate that came to be 951 writes/min. In other words, without partition-

ing, this would be the peak traffic that a single machine would have to handle.

In Fig. 4 we plot the CCDF of the write request (tweets arrival) per min across all partitions for different partition sizes (8,32,128 respectively). For 8 machines (Fig. 4 (a)), the 99.99% percentile peak of traffic is 136, 171, 246 req/min for Random, MO+ and GP respectively. After partitioning the machines only need to have resources to deal with this reduced load peak. For the partition in 128 machines (Fig. 4 (c)) the load peak is 21,35,28 req/min for Random, MO+ and GP.

The picture that emerges from our experiments is as follows. Schemes based on modularity optimization are good for reducing network traffic, and are competitive with Random in terms of load balancing across partitions. Hence while the tradeoff between reducing bandwidth costs and balancing load is still present, we find that MO based schemes are promising. We interpret these results in light of the arguments we made in Sec 3.3, more specifically the existence of social conversations, and the community structure.

5. DISCUSSION

Online social networks are increasing at a very high rate, putting a strain on existing infrastructure and demanding new architectural solutions. As such systems get pushed to highly distributed cloud infrastructure, the problem of finding intelligent solutions to scaling issues is further exacerbated.

In this paper we explored the problem of partition the users' space of different OSN using different schemes. By using data from real OSN – Twitter and Orkut we measured the impact of different partition schemes on network traffic and peak load. We found that traditional graph partitioning techniques can effectively be applied to OSNs to reduce the network overhead that a typical off-the-shelf random partition would generate while maintaining an acceptable peak load distribution. We also show that modularity optimization algorithms are even better suited to the social network partition problem given that they are based on finding 'community' structures in the network. Such a scheme, however, presents the problem of producing arbitrary number of communities and we propose a post-processing algorithm MO+ to handle this issue.

³Note that a tweet is a write request, it has to be stored and distributed. Read operations are more common but require much less resources since systems are designed for faster reads. Common practice is that the QoS of a read request should be < 200ms, while for a write it can be an order of magnitude higher.

6. REFERENCES

- L. Backstrom, D. Huttenlocher, J. Kleinberg, and X. Lan. Group formation in large social networks: membership, growth, and evolution. In KDD '06: Proceedings of the 12th ACM SIGKDD international conference on Knowledge discovery and data mining, pages 44–54, New York, NY, USA, 2006. ACM.
- [2] V. D. Blondel, J.-L. Guillaume, R. Lambiotte, and E. Lefebvre. Fast unfolding of communities in large networks. *J.STAT.MECH.*, page P10008, 2008.
- [3] H. Chun, H. Kwak, Y.-H. Eom, Y.-Y. Ahn, S. Moon, and H. Jeong. Comparison of online social relations in volume vs interaction: a case study of cyworld. In IMC '08: Proceedings of the 8th ACM SIGCOMM conference on Internet measurement, pages 57–70, New York, NY, USA, 2008. ACM.
- [4] K. Church, A. Greenberg, and J. Hamilton. On delivering embarrassingly distributed cloud services. In ACM HotNets VII, 2008.
- [5] S. Golder, D. M. Wilkinson, and B. A. Huberman. Rhythms of social interaction: messaging within a massive online network, 2006. cite arxiv:cs.CY/0611137.
- [6] A. Greenberg, J. Hamilton, D. A. Maltz, and P. Patel. The cost of a cloud: research problems in data center networks. SIGCOMM Comput. Commun. Rev., 39(1):68-73, 2009.
- J. Hamilton. Geo-replication at facebook. http://perspectives.mvdirona.com/2008/08/21/ GeoReplicationAtFacebook.aspx.
- [8] J. Hamilton. Scaling linkedin. http://perspectives.mvdirona.com/2008/06/08/ ScalingLinkedIn.aspx.
- [9] R. Kannan, S. Vempala, and A. Vetta. On clusterings: Good, bad and spectral. J. ACM, 51(3):497–515, 2004.
- [10] G. Karypis and V. Kumar. A fast and high quality multilevel scheme for partitioning irregular graphs. SIAM J. Sci. Comput., 20(1):359–392, 1998.
- [11] G. Kossinets, J. Kleinberg, and D. Watts. The structure of information pathways in a social communication network. In KDD '08: Proceeding of the 14th ACM SIGKDD international conference on Knowledge discovery and data mining, pages 435–443, New York, NY, USA, 2008. ACM.
- [12] B. Krishnamurthy, P. Gill, and M. Arlitt. A few chirps about twitter. In WOSP '08: Proceedings of the first workshop on Online social networks, pages 19–24, New York, NY, USA, 2008. ACM.
- [13] N. Laoutaris, P. Rodriguez, and L. Massoulie. Echos: edge capacity hosting overlays of nano data centers. SIGCOMM Comput. Commun. Rev., 38(1):51–54, 2008.
- [14] J. Leskovec, K. J. Lang, A. Dasgupta, and M. W. Mahoney. Community structure in large networks: Natural cluster sizes and the absence of large well-defined clusters. CoRR, abs/0810.1355, 2008.
- [15] D. Liben-Nowell, J. Novak, R. Kumar, P. Raghavan, and A. Tomkins. Geographic routing in social networks. *Proceedings of the National Academy of Sciences*, 102(33):11623–11628, Aug. 2005.
- [16] N. Media. Global faces and networked places. http://blog.nielsen.com/nielsenwire/wp-content/uploads/ 2009/03/nielsen_globalfaces_mar09.pdf.
- [17] N. Media. Growth of twitter. http://blog.nielsen.com/nielsenwire/online_mobile/ twitters-tweet-smell-of-success/.
- [18] A. Mislove, H. S. Koppula, K. P. Gummadi, P. Druschel, and B. Bhattacharjee. Growth of the

- flickr social network. In WOSN '08: Proceedings of the first workshop on Online social networks, pages 25–30, New York, NY, USA, 2008. ACM.
- [19] A. Mislove, M. Marcon, K. P. Gummadi, P. Druschel, and B. Bhattacharjee. Measurement and analysis of online social networks. In IMC '07: Proceedings of the 7th ACM SIGCOMM conference on Internet measurement, pages 29–42, New York, NY, USA, 2007. ACM.
- [20] M. Newman and J. Park. Why social networks are different from other types of networks. *Phys. Rev. E*, 68:036122, 2003.
- [21] M. E. J. Newman. Modularity and community structure in networks. PROC.NATL.ACAD.SCI.USA, 103:8577, 2006.
- [22] J. Oh, A. Susarla, and Y. Tan. Examining the diffusion of user-generated content in online social networks. SSRN eLibrary, 2008.
- networks. SSRN eLibrary, 2008.
 [23] D. A. Spielman and S.-H. Teng. Nearly-linear time algorithms for graph partitioning, graph sparsification, and solving linear systems. In STOC '04: Proceedings of the thirty-sixth annual ACM symposium on Theory of computing, pages 81–90, New York, NY, USA, 2004. ACM.
- [24] D. A. Spielman and S.-H. Teng. A local clustering algorithm for massive graphs and its application to nearly-linear time graph partitioning. *CoRR*, abs/0809.3232, 2008.
- [25] M. Valafar, R. Rejaie, and W. Willinger. Beyond friendship graphs: A study of user interactions in flickr. In WOSN '09, pages 25–30, New York, NY, USA, 2009. ACM.
- [26] D. Watts. Network dynamics and the small world phenomenon. Americal Journal of Sociology, 105(2):493–527, 1999.
- [27] Y. Zhao, Y. Xie, F. Yu, Q. Ke, Y. Yu, Y. Chen, and E. Gillum. Botgraph: Large scale spamming botnet detection. In NSDI'09: Proceedings of the 5th USENIX Symposium on Networked Systems Design and Implementation, Berkeley, CA, USA, 2009. USENIX Association.